Multidimensional Measurement of Sectoral Performance: Evidence from Public Schools in Pakistan*

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Abstract

I develop a tool for measuring the multidimensional performance of the public sector in the spirit of multidimensional measures of poverty, and apply it to the case of public education in Pakistan. The framework allows fiscally constrained policymakers and relevant development practitioners to measure a sector's resource base, follow it over time, and optimize targeting of resources. The measure's decompositional properties provide for easy identification of the sources of deprivation along various dimensions and across subgroups, such as geographical areas and subsectors. In an application to the public education sector in Sindh province, Pakistan, I show that 27 percent of public schools are multidimensionally deprived and the weakest dimensions are physical infrastructure and facilities. Single-sex, rural schools, where instruction is in the native Sindhi language contribute the most to the overall deprivation measurement. Such identification permits efficient allocation of policy attention. Targeting public resources to these weak links can generate the biggest bang for the buck. This is especially valuable in resource-constrained, developing countries. The measure allows policymakers to glean critical sectoral information from the din of administrative and survey data.

Keywords: Sectoral deprivation; multidimensional measurement; targeted policymaking; decompositions; education; Asia; Pakistan

JEL Classification: H41, H82, I24, I25, I32

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Introduction

Fiscal constraints in developing countries present a dual challenge. On the one hand, developing countries require significant investments across public and private sectors to catch up with industrialized countries. Such investments are difficult to make under a highly constrained resource base. Due to a lack of such investments, governments in developing countries have a hard time creating future fiscal space, leading to a vicious cycle of low investments and poor public sector health and performance. Given the scarcity of resources, it becomes imperative that the state has access to low-cost analytical tools to allow it to identify sectoral dimensions and geographic regions that are the most deprived, and to funnel public investments into these subgroups and dimensions to optimize limited public investments.

An important strand of development literature over the past decade has experimented with the use of measures that capture multiple dimensions when assessing the level of deprivation of an individual or a group of individuals. For example, in the measurement of poverty, it is now widely accepted that a unidimensional approach focusing on income levels is insufficient. $n - 1$ other dimensions such as health, education and nutrition, among others, factor into the "well-being" of an individual – leading to the well-documented multidimensional approach to the measurement of poverty. The Alkire-Foster measure of multidimensional poverty developed by Sabina Alkire and James Foster (2011) is such an approach.

Alkire and Foster apply their method to measuring aggregate multidimensional poverty, factoring in a number of "functionings" (dimensions), weights associated with these dimensions indicating their relative importance, and cutoffs – particular measures beyond which an individual is considered poor in a given dimension. The choice of dimensions, weights and cutoffs is flexible. This flexibility allows for a process of democratic deliberation and consensus-formation, leading to choices that are reflective of a country or region's context, and its ethical and normative standpoints.

Further, the Alkire-Foster method provides a powerful tool for policymakers to make intra- and inter-country comparisons, as well as comparisons across different subgroups via decompositional properties built into the tool. I contribute to this literature by expanding the use of the Alkire-Foster method which studies poverty levels with the use of individual-level data, to analyzing the health of a sector with the use of sectoral, unit-level data. More specifically, for this paper, I build a multidimensional measure of sectoral deprivation, called the Multidimensional Sectoral Deprivation Index ($MSDI$). The method can be used to measure sectoral health at the aggregate level, which can also be decomposed for better targeting of resources.

As proof-of-concept, I consider the public education sector, develop a methodology for assessing its readiness, and apply the method to the case of Sindh province in Pakistan. Broadly, countries are on either one of two, broad trajectories in the education sector: those in the developed world where educational infrastructure is robust – with some variation – and focus has shifted to the provision of sophisticated pedagogical improvements, school-based nourishment programs and the use of high-end technology for assistive learning; and those in low-resource, education-poor developing countries where issues related to poor school infrastructure, low enrolment, teacher absenteeism, and poor learning quality are pervasive.

For schools on the former trajectory of education growth, indicators such as the availability of a school building are not very informative. For these schools, the more relevant indicators are class atmosphere, consensus and cooperation amongst teachers, and positive reinforcement of students (Nordenbo et al., 2010). On the other hand, for schools on the latter trajectory, when there exists a lack of qualified teachers and/or high levels of teacher absenteeism, and one-teacher schools, consensus and cooperation amongst teachers becomes a second-order issue.

While development studies as those documented in Glewwe et al. (2012) provide substantial internal validity and shine a light on critical inputs, policymakers need as part of their toolkits, ways of measuring education sector health when external validity is not well established. Given that different factors affect school outcomes differentially, with heterogeneity of impact across regions, capturing a diverse set of dimensions is critical to measuring the quality of overall educational infrastructure in a geographical region.

Section I presents the conceptual framework for the construction of $MSDI$, together with its properties of decomposability and a comparison with alternate approaches. In Section II, I will discuss the context in which I apply this tool, including the source and nature of the data used, and the choice of dimensions, weights and cutoffs. Section III provides results of the application of the $MSDI$, followed by Section IV where I conduct a sensitivity analysis of these empirical results. Section V concludes the discussion.

I Methodology

I.A Construction of the Multidimensional Sectoral Deprivation Index (MSDI)

In constructing the $MSDI$, I borrow from the framework developed by Alkire and Foster (2007). For the purpose of this paper, I will restrict the analysis to the use of the M_0 measure. M_0 is known as the adjusted poverty headcount ratio, and it provides an index of multidimensional poverty. In my setting, the $MSDI$ is the analog of the M_0, and serves as the multidimensional sectoral deprivation index. In this section, I will formally discuss censoring of the characteristics matrix, cutoffs, weights for each dimension, and the calculation of the simple $MSDI$.

We begin with a basic set up. $i = 1,2, \dots, n$ indexes sectoral units, while $j = 1,2, \dots, d$ indexes specified dimensions. I set up a sectoral unit achievement matrix X, with each element represented by ij, or sectoral unit i's performance on dimension j. Sectoral units can comprise bus and train stations in the transportation sector, factories in the manufacturing sector, hospitals in the health sector, or schools in the public education sector.

For the purpose of identifying "deprivation" within a given dimension, I specify a cutoff vector z, with z_j serving as the cutoff for each dimension j. For each x_{ij}, in achievement matrix X, I replace the value of x_{ij} with a 0 when $x_{ij} \leq z_j$, and with a 1 when $x_{ij} > z_j$. This transforms the achievement matrix X into the deprivation matrix g^0, with each g_{ij}^0 indicating whether sectoral unit i is deprived in dimension j. This serves as the first round of *censoring*, in that, it suppresses the *level* of deprivation and exclusively focuses on a binary indicator for the *presence* of deprivation of a sectoral unit within a given dimension.

From g^0, I construct a column vector c' of deprivation counts, with ${c_i}' = \sum_{j=1}^{d} g_{ij}^0$. Each element of c' provides the count for dimensions in which sectoral unit i is deprived. However, given that all dimensions might not hold the same relative importance in contributing to the deprivation of a given sectoral unit, based on empirical evidence and/or normative considerations, a flexible weighting scheme is used for the d dimensions, defined by the vector $w = [w_1\ w_2 \ldots w_d]$. These weights do not necessarily have to sum to 1 but are normalized for convenience. Using these weights, I construct a deprivation score vector c for each sectoral unit, as $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$.

The next step is to identify a given sectoral unit as being either multidimensionally deprived, or non-deprived. An identification function $\rho_k(x_i; z)$ takes a value of 1 if a sectoral unit is multidimensionally deprived, or 0 if it is not. The *intersection* approach implies that a sectoral unit be considered multidimensionally deprived only if it is deprived in all dimensions, so that $\rho_k(x_i; z) = 1$ if $c_i = 1$, or 0 otherwise. So even a sectoral unit which is deprived in $d - 1$ dimensions will be captured as being multidimensionally non-deprived. On the other extreme, the *union* approach would imply that $\rho_k(x_i; z) = 1$ if $c_i \geq 0$, and 0 otherwise. In this case, a sectoral unit which is deprived in at least one dimension will be identified as being multidimensionally deprived.

While both approaches have their merits in different settings, given that a number of factors combine to optimize the performance of a given sector, an intermediate approach appears to be more suitable. This approach uses a cutoff k with $k \in [0,1]$, above which, a sectoral unit is termed as multidimensionally deprived. As with the dimensional cutoff z, the choice of k is flexible, as discussed in the following sections. In this case, the identification function $\rho_k(x_i; z) = 1$ if $c_i \geq k$, and 0 otherwise.

Using the dual cutoff-identification approach, I construct the censored deprivation matrix $g^0(k)$, with $g_{ij}^0(k) = \rho_k(x_i; z) * g_{ij}^0$. Thus, if a sectoral unit is multidimensionally non-deprived, then its deprivation in all individual dimensions is suppressed to 0. This is an important step and allows the $MSDI$ to focus on the extent of deprivation of deprived sectoral units, and not be affected by changes in the deprivation level of non-deprived sectoral units. Similarly, the vector of censored deprivation scores is constructed using $c_i(k) = \sum_{j=1}^{d} w_j g_{ij}^0\,(k)$.

Aggregating the censored deprivation scores, I calculate the $MSDI$ as the mean of the censored deprivation score vector:

$$MSDI = \frac{1}{n} \times \sum_{i=1}^{n} c_i(k)$$

The $MSDI$ can also be expressed as the product of the deprivation incidence H (fraction of sectoral units that are deprived) and the deprivation intensity (A), or the average deprivation score among deprived sectoral units:

$$MSDI = H \times A = \frac{q}{n} \times \frac{1}{q} \sum_{i=1}^{q} c_i(k)$$

Another interpretation of MSDI is that it provides the share of weighted deprivations experienced by the deprived divided by the maximum possible deprivations that could be experienced if all sectoral units were deprived in all dimensions.

$$MSDI = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{d} w_j g_{ij}^0(k)$$

It is important to note that for any specified weighting and cutoff scheme, the $MSDI$ satisfies decomposability, replication invariance, symmetry, deprivation focus, weak and dimensional monotonicity, nontriviality, normalization, and weak rearrangement, discussed in detail in Alkire-Foster (2011).

I.B Decomposability

Subgroup Decompositions

In this paper, I will exploit the $MSDI's$ decomposability property extensively to unpack heterogeneity in deprivation across subgroups and dimensions. The ability to do so follows from the flexibility afforded by the $MSDI$ for both subgroup as well as dimensional decomposability. Here, I briefly discuss the mechanics of the tool's decomposition property, and how this affects the analysis in the following sections.

Subgroups can include different administrative regions such as states, provinces, counties, districts, villages, and cities, as well as groupings based on classifications, for example, in the case of the education sector, urban-rural, school gender, and primary medium of instruction, among others. I index each subgroup by $s = 1, \ldots, m$, with the population share of the subgroup given by $p^s = n^s/n$. Further, we can divide achievement matrix X into its different constituent subgroups, each indexed by X^s. By repeating the process outlined in the previous section, I compute the $MSDI$ for each of these constituent achievement sub-matrices ($MSDI(X^s)$). So the overall $MSDI$ can be expressed as:

$$MSDI(X) = \sum_{s=1}^{m} p^s * MSDI(X^s)$$

A noticeable property of this expression is that it is additive. Using this property, the contribution of each subgroup to overall sectoral unit deprivation can be calculated as follows:

$$D_s^0 = p^s \frac{MSDI(X^s)}{MSDI(X)}$$

Where,

$$\sum_{s=1}^{m} D_s^0 = 1$$

The contribution of a given subgroup s depends both on its population share, as well as its $MSDI$ as a fraction of overall $MSDI$, with $\frac{\partial D_s^0}{\partial p^s} > 0$ and $\frac{\partial D_s^0}{\partial MSDI(X^s)} > 0$. If sectoral deprivation is distributed uniformly across the population of sectoral units, then $p^s = D_s^0$, implying that the population share of the subgroup will be equal to the subgroup's share of aggregate sectoral deprivation. In reality, there will be heterogeneous distribution of deprivation burden across subgroups. Therefore, cases where $p^s < D_s^0$ allow me to pinpoint subgroups for which, the contribution to sectoral deprivation is disproportionately higher than the subgroup population size. This provides a useful policy device to pinpoint stragglers and devise more effective, targeted policies to improve overall sectoral health and performance.

The cardinality of the measure is useful in comparing different subgroups – for example, geographic regions – as well as comparing dimensional contributions. The $MSDI$ of a sectoral unit is simply the $MSDI(x)$ of a submatrix which is a singleton and is equivalent to the sectoral unit's censored deprivation score. Similar to the overall $MSDI$, the censored deprivation score of each sectoral unit provides a cardinal ranking of sectoral units along the deprivation spectrum. Meaningful information can be gleaned by comparing which dimensions the sectoral units are deprived in. The next section provides further details.

Dimensional Decompositions

The $MSDI$ can also be used to decompose a dimension's contribution to the overall sectoral deprivation level. Without loss of generality, the additive nature of the $MSDI$ allows it to be expressed as the weighted sum of each dimensional censored headcount ratio $h_j(k)$, where $h_j(k) = \sum_{i=1}^{n} g_{ij}^{0}(k)$. Intuitively, the censored headcount ratio of each dimension j is the proportion of the population of sectoral units that is identified as deprived, and further, the fraction that is deprived in dimension j. Therefore, the $MSDI$ can be expressed as:

$$MSDI = \sum_{j=1}^{d} w_j * h_j(k)$$

Under the restriction $w_1 = \cdots = w_d$, this expression collapses to:

$$MSDI = w \sum_{j=1}^{d} h_j(k)$$

If weights are not uniform, then the contribution of each dimension to overall sectoral deprivation not only depends on each dimension's censored headcount ratio, but also the weights associated with it. More formally,

$$\lambda_j^0(k) = w_j \frac{h_j(k)}{MSDI}$$

Two dimensions can have the same censored headcount ratio, $h_j = h_{-j}$. However, if $w_j > w_{-j}$, then $\lambda_j^0 > \lambda_{-j}^0$. In the case of uniform weights, equal h implies the same dimensional contribution to overall sectoral deprivation.

Dimensional decomposition provides a tool to policymakers to focus their attention on dimensions that are contributing disproportionately to overall sectoral deprivation, as compared to the weights associated with them. This allows policymakers to target dimensions that are acting as weak links in the system. Further, dimensional decompositions can be combined with subgroup decompositions, allowing policymakers to focus on the performance of specific dimensions within a subgroup. Under highly constrained resources, the ability to do this is critical for allocating and utilizing taxpayer money most efficiently.

I.C Comparison to Alternative Approaches

Other approaches to ranking the health of educational units such as schools include the use of production efficiency techniques such as data envelopment analysis (DEA) and stochastic frontier analysis (SEA). These methods can handle multiple inputs and outputs to establish a production frontier to measure technical and allocative efficiency of individual sectoral units. Loosely, the distance of a unit from the frontier provides a measure of the unit's relative inefficiency. A representation of SFA and DEA-based frontiers is provided in Figure 1.

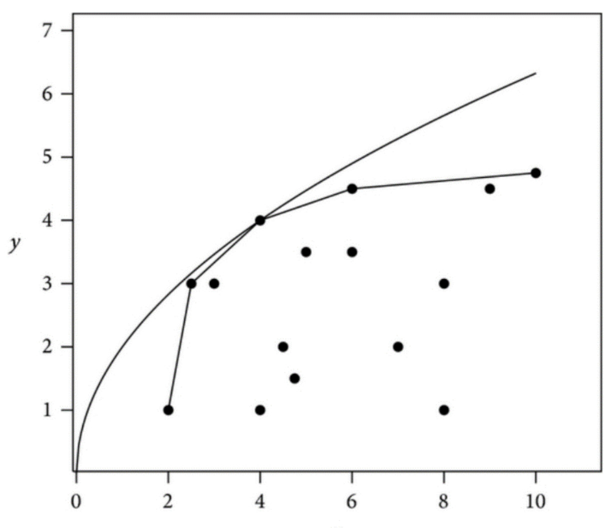

Figure 1: Data Envelopment Analysis (DEA) versus Stochastic Frontier Analysis (SFA)

(Source: Aparicio et al., 2014)

However, these methods come with several shortcomings, and might not be best aligned with the aim of this analysis, which is to focus on the most low-resource sectoral units and construct a ranking which is unaffected by high-resource units. Firstly, as a non-parametric approach which does not require assumptions regarding the functional form of the frontier, DEA is a valuable analytical tool and useful in supporting practical decision-making in situations such as reducing inefficiencies of sectoral units. However, the approach requires distribution and production assumptions, which if inaccurate, can generate a bias over the frontier. Since the DEA models in current use provide only a limited range of production assumptions, they are hard to test.

Small unit bias has also been observed in prior studies using DEA, with units that are small appearing to be relatively less inefficient, systematically. Further, the number of units on the efficient frontier is found to be an increasing function of the number of input and output variables (Berg, 2010). In terms of our study, another issue which arises with ranking sectoral using DEA is that the approach uses observed observations with input-output bundles to form the frontier. Thus, using the example of the public education sector in Sindh province, Pakistan, ranking of schools using this approach would be solely based on schools in Pakistan on the frontier, with benchmarking used to evaluate potential changes in the bundle of inputs. However, given that low-resource, poorly performing countries such as Pakistan aspire to reach international standards, without comparable data on schools – and their input-output bundles which have reached such levels under a similar context, the frontier used for ranking schools might not be the correct one to use.

Worth noting is that DEA analyses are sensitive to the selection of inputs and outputs, similar to the $MSDI$. Eventually, the tool to be used should be aligned with both the existing sectoral capital in a given location, as well as feasibility for data collection and administrative rollout.

II Application: Public Education in Sindh, Pakistan

II.A Overview of Pakistan's Education Sector Performance

Over the last decade, Pakistan's economy has shown significant growth. Real GDP has increased at a rate close to four percent since 2010. However, the country's expenditure on education has stagnated, staying at less than two percent of GDP. Under such conditions, Pakistan did not meet its objective of providing universal primary education by 2015 under the Millennium Development Goals (MDG). In fact, close to one-third of all primary school-age children in Pakistan remained out of school (UNESCO, 2015). Even for those who were enrolled in primary school at least once, approximately 38 percent dropped out (UNDP HDR, 2015). For the stayers, basic numeracy and language skills remained lower than the grade level in which they were enrolled (Andrabi et al., 2013). Dysfunctional schools[1], a dearth of necessary school infrastructure, and teacher absenteeism adversely impact quality of learning at schools (Dundar et al., 2014). The overall performance in the education sectors also masks significant heterogeneity across provinces, and across urban and rural districts within provinces.

Sindh province, with a population of 42.4 million[2], is the second-largest province of Pakistan, and is a particularly resource-constrained province that faces large deficits in public service delivery. The Annual School Census (2014-15) put the number of public schools in the province at 46,071. With 1.08 schools per 1,000 inhabitants, the province has one of the densest public schooling systems in the world. But while there are a large number of schools on paper, many of these schools do not function in reality. Approximately 15 percent of schools in rural areas have either been closed for six months or more, have no students enrolled in them, or do not have teachers assigned to them, according to the ASC, leading to the phenomenon known as "ghost schools".

[1] A school being functional refers to schools being open with teachers and students registered at the time of the Annual School Census (ASC) of 2014-15.
[2] The population of Sindh is roughly one-quarter of Pakistan's total population.

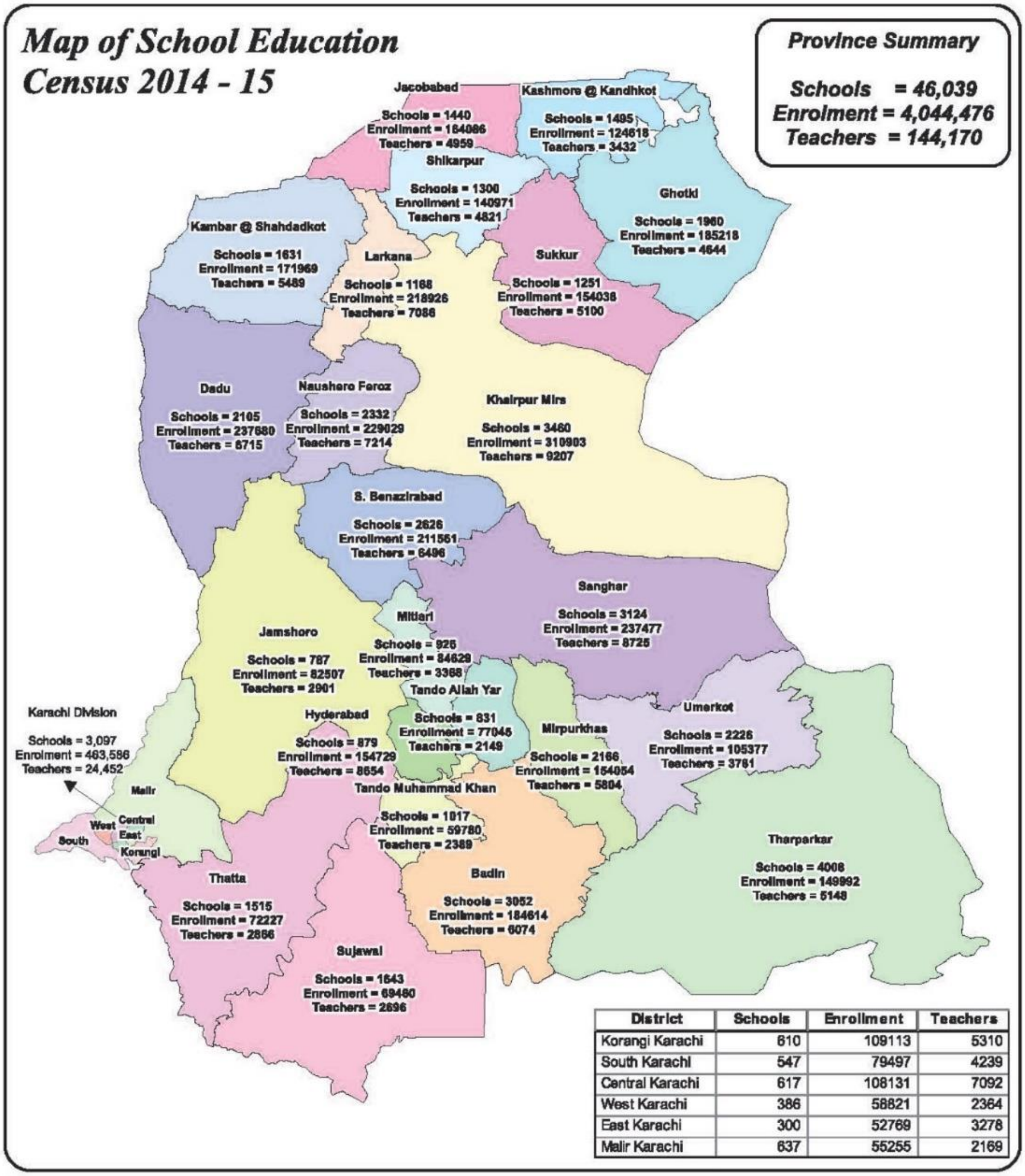

Figure 2: Sindh Province with its Districts

Across schools that are functional in rural Sindh, 57 percent of schools only have one teacher assigned to them. Annual Status of Education Report (ASER) Pakistan's 2015 survey reveals that teacher absenteeism hovers around 12 percent for public primary schools. In terms of physical infrastructure, a quarter of schools in Sindh either do not have a school building, or even when a school building exists, it lacks access to facilities such as drinking water, electricity, functioning bathrooms and boundary walls.

Along with poor infrastructure and an endemic shortage of teachers, rural Sindh also has low student enrollment rates. According to results from the Pakistan Social and Living Standards Measurement Survey (PSLM 2014-2015), only 61 percent of all Sindhi children ages 6-10 are enrolled in school at the primary level. The net enrollment rate is 73 percent in urban areas in Sindh province, compared to 77 percent in all of urban Pakistan. The net enrollment rate drops to 52 percent in rural areas in Sindh, compared to 63 percent in all of rural Pakistan.

Students' learning levels in Sindh province correspond to the inadequate investment and inputs in public education. According to the ASER Pakistan's 2015 survey, only 24 percent of Grade 3 students can read words in English, while only 19 percent of Grade 5 students can read full sentences. For Math, learning outcomes are slightly better: 32 percent of Grade 3 students can subtract, while 33 percent of Grade 5 students can perform division. For both subjects, boys outperform girls by six percentage points. These poor learning outcomes can also be partially explained by the fact that on average, only 17 percent of the students' mothers and 44 percent of their fathers have attained at least primary schooling (ASER 2015). The institutional structure of the educational system in Sindh is detailed in Appendix 1.1.

II.B Data

The Annual School Census (ASC) collects information on all public schools in the province, consolidated via the Sindh Education Management Information System (SEMIS). Details on the history and mechanics of SEMIS are provided in Appendix 1.2. These schools include primary, elementary, middle, secondary, and higher secondary schools; boys, girls and mixed schools; schools located in urban and rural areas; and schools that use either English, Urdu or Sindhi as the primary medium of instruction. Data is collected on school characteristics including functionality, ownership status, infrastructure, classroom equipment, additional facilities such as labs and playgrounds, teachers, students, School Management Committees (SMC)[3], and SMC funding.

The ASC data used for this paper comes from the comprehensive survey conducted by the Sindh Government's Reform Support Unit (RSU) during FY 2014-15 and contains 46,071 unique schools. Of these schools, 10,625 schools are boys-only schools, 7,069 are girls-only schools, and 28,377 are co-educational schools. 41,364 of these schools are in rural areas, while only 4,707 are in urban areas. 41,721 contain primary-level classes, 1,788 contain middle-level classes, 538 contain elementary-level classes, 1,729 contain secondary-level classes and 295 contain higher secondary-level classes. These are not mutually exclusive categories, since many schools can have all levels of education, while others are restricted to specific levels, for example, primary-level schooling. A majority of schools in our data use Sindhi as the primary medium of instruction.

Indicators on which data is collected have largely remained unchanged over the past few years. Therefore, while I utilize an annual cross-section of the ASC data for testing and recalibrated the $MSDI$, the analysis can be expanded to cover multiple years. Importantly, a similar Annual School Census with analogous data collection tools is conducted in Punjab province, the largest province of Pakistan, with an estimated population of 100 million people, as well as in Khyber-Pukhtunkhwa (KPK) and Balochistan provinces. This generates potential for the application of the tool both across time and provinces.

II.C Choice of Dimensions: Public Education in Sindh

In this subsection, I expand on the framework established above and provide the rationale for the choice of dimensions related to the public education sector in Sindh, Pakistan. In terms of choosing dimensions for the $MSDI$, I engage intensively with existing development literature

[3] School Management Committees (SMC) are community platforms for parents, teachers and other community members to foster a dialogue on the status of schools and education at the local (village/neighborhood) level. SMCs are recognized by the provincial government, with each SMC related to a primary school receiving PKR 22,000 (approximately USD 200) annually. Executive body members are elected by the community, and are responsible for infrastructure funding, temporary hiring of additional teachers and augmenting transportation options to bring children to school through the use of publicly formulated School Improvement Plans (SIPs).

to identify dimensions which have a positive impact on educational outcomes. Firstly, I look at impact evaluations across developing countries by using reviews of studies exploring the impact of educational inputs and processes on school outcomes. While these individual studies can have strong internal validity, their external validity in a region with a large number of schools in culturally, geographically, climatically, and linguistically distinct sub-regions is weak. Therefore, relying on individual studies or studies conducted in distinct regions to extrapolate over the functioning of all schools in Sindh province requires strong assumptions related to the generalizability of results of these experiments and quasi-experiments. However, the rich corpus of these studies provides evidence on the range of dimensions that have an impact on key schooling outcomes broadly, under relatively similar conditions.

I focus my attention on Glewwe et al. (2012) and the International Initiative for Impact Evaluation's (3ie) systematic review of "the impact of education programmes on learning and school participation in low- and middle-income countries" (2016). Glewwe et al. review a large number of articles and working papers (total of 9,000), concentrating on 79 papers that are relevant to a developing country context, and which use econometric techniques (such as randomized controlled trials, regression discontinuity design, difference-in-differences, matching, and ordinary least square analysis) to assess the impact on student educational outcomes of school infrastructure and pedagogical supplies, teacher and principal characteristics, and/or school organization. Of these, a total of 43 papers are classified as "high-quality", if they used robust identification strategies. The three key areas that seem to work broadly are:

1. School infrastructure and pedagogical materials (electricity, roof/wall/floor, desks/tables/chairs, blackboard, textbooks, library, computers, etc.)
2. Teacher and principal characteristics (education, training, experience, sex, subject knowledge, and ethnicity)
3. School organization (pupil-teacher ratio, teaching methods, teacher absence, homework assignment, student assessment methods, teacher contract, expenditure per pupil, etc.)

Two key outcomes that researchers have looked at are student test scores, and time spent by students in school. The focus in this paper is on the inputs that most affect these two outcomes. Restricting the sample to the 43 shortlisted, high-quality studies, Glewwe et al. find the following results:

Table 1: Indicators and their impacts on key student outcomes

Sr. #	Indicator	Impact on Student Test Scores	Impact on Student Time in School
1	Desks/tables/chairs	Positive	N/A
2	Blackboards	Positive	N/A
3	Libraries	Positive	N/A
4	Roof/wall/floor	Positive	Positive
5	Teacher knowledge	Positive	N/A
6	Teacher training	Positive	Negative
7	Teacher presence	Positive	N/A
8	School meals	Positive	N/A
9	Hours of school day	Positive	N/A
10	Tutoring	Positive	N/A
11	Textbooks/workbooks	Mixed	Positive
12	Computers lab	Mixed	N/A
13	Electricity	Mixed	N/A
14	Teacher education level	Mixed	Positive
15	Teacher experience	Mixed	Mixed
16	Student-teacher ratio	Mixed	Positive
17	Multi-grade teaching	Mixed	N/A
18	Contract teacher	Mixed	N/A

Therefore, amongst the above-mentioned indicators, those related to basic infrastructure appear to have mostly positive impacts on key student outcomes, while other teacher and school organization-related indicators have positive, or mixed results.

Complementary to the above-mentioned review, the International Initiative for Impact Evaluation's (3ie) systematic review synthesizes evidence from 216 education-related programs covering approximately 16 million children across 52 lower and middle-income countries. Besides considering a wider range of studies, the studies reviewed by 3ie follow robust methodologies, and assess impact of inputs and processes on a range of outcomes, such as math scores, language, enrollment, attendance, dropout and cognitive outcomes. The metaanalysis found that the following factors seemed to work, or were promising: merit-based scholarships, school-feeding, cash transfers, public-private partnerships, community-based monitoring, remedial education, new schools and infrastructure, structured pedagogy, and extra time in school. The impacts of other factors were less clear.

Recent literature from Pakistan – mostly gathered as part of Learning and Educational Achievement in Punjab Schools (LEAPS) – shows that school quality affects the demand for schooling and evaluates the magnitude of this relationship. LEAPS data includes both public and private schools. Since the public schooling system is free, parents' demand for better schools can be proxied by their willingness to pay for private schools (via changes in fee) for improved schooling services. Andrabi et al. (2017) find that the equivalent impact of a one standard deviation increase in an index of basic infrastructure (rooms, chairs, blackboards, and other non-building material) leads to a 0.07 standard deviation increase in fees (PKR 55), while a one standard deviation increase in advanced infrastructure (such as a library, fans, or computer facility) leads to a 0.17 standard deviation (Rs 141) increase. Similarly, Carneiro et al. (2013) find that school attributes such as facilities, teacher attributes (the proportion of female teachers, the proportion of teachers with a university degree and the proportion of teachers with at least 3 years of experience), and permanent classrooms affect parents' willingness to pay. There is heterogeneity in these effects, both across boys and girls schools, as well as along different parts of respective distributions.

Thus, there is a noticeable consensus that emerges from these meta-studies. Improvements in basic infrastructure, reduction in teacher absenteeism, improvement in teacher quality, and increase in community engagement and monitoring seem to positively impact key student outcomes. These are, therefore, promising dimensions that should be included in any index for measuring the health of the education sector.

In the best-case scenario where these studies have strong external validity, improvements along any of these dimensions should lead to better outcomes. In the worst-case scenario where these studies have poor external validity, there is no guarantee that these dimensions will lead to better outcomes. To hedge for this, I take a conservative approach in measuring deprivation by considering basic schooling inputs provisions. These include, among others, the provision of shelter, a teacher being present in the classroom, and chairs for all students to sit on.

Critically, basic indicators that are seemingly relevant in the context of developing countries, and in Pakistan's case specifically, are covered under the data collection exercises of provincial governments in Pakistan. Consolidating indicators having a positive impact on school and student outcomes, and comparing these with data available from Sindh province, I finalize a set of 23 indicators, clustered under five disparate dimensions. These dimensions include school status; infrastructure and facilities; teachers; classrooms; and community engagement. Table 2 provides further details. For example, teacher qualification is an indicator within the teacher dimension of school resources, while availability of blackboards is an indicator within the classroom dimension of school resources.

Table 2: Description of Dimensions, Indicators, and Cutoffs

	Dimensions				
	School Status	**Infrastructure and Facilities**	**Teachers**	**Classrooms**	**Community Engagement**
Indicators	Functional	Building structure	Teacher qualification	# of Classrooms	School Management Committee (SMC) functional
		Boundary wall	Teacher experience	Room utilization	SMC funds
		Electricity	Total # of teachers	Students per classroom	
		Fans	Student-teacher ratio	Blackboard	
		Facilities Index		Chairs for students	
		Toilets		Desks for students	
		Student-functional toilet ratio		Chairs for teachers	
		Water		Desks for teachers	

While I have engaged existing literature to establish relevant indicators, I have to omit some indicators that the literature suggests should be added, but for which, the Sindh government does not collect information. For example, in terms of teacher quality, it is worthwhile knowing what the teachers were doing at the time of the data collection visit. While such intensive data is collected for impact evaluations conducted in Sindh province by other non-governmental and/or multilateral organizations such as the World Bank, this data is not collected by the government during the ASC. There is a tradeoff between using either of these two kinds of datasets. While richer data from these impact evaluations can be used to cover more indicators when assessing school deprivation levels in select districts of Sindh province, a focus on a limited number of subgroups prevents the tool's subgroup decompositional abilities to be exploited optimally. Moreover, of interest are trends in school deprivation across time, for which such intensive data is unavailable. Standardized data collected regularly under the ASC allows for the establishment of a set of basic indicators which can be used flexibly for subgroup, as well as intertemporal sectoral health tracking.

II.D Choice of Weights and Cutoffs

This section details the selection of weights accorded to each indicator, as well as the cutoff below which a sectoral unit – school, in this application – is marked as being deprived. It is important to highlight the flexible nature of the selection of weights associated with each dimension. The selection of these weights depends on empirical findings, normative and political economy considerations, as well as participation in and implementation of international accords.

For simplicity, I begin the application of the $MSDI$ on schools in Sindh using uniform weights. While this approach allows me to control for variation in weights to focus on other sources of variation such as dimensional and subgroup impacts on the $MSDI$, the use of uniform weights is a first step. After preliminary analysis, I allow for a more flexible approach containing minimal restrictions on weights, by simulating the distribution of the $MSDI$ over a range of weights in Section IV. I begin the analysis by giving weights equal to 1/23 to each of the twenty-three indicators.

The two stages of cutoff selection include setting cutoffs z_j for each dimension j, so that school i can be considered as deprived in that dimension, based on the school's performance on that dimension, and then selecting a cutoff k for the multidimensional deprivation of school i based on the overall deprivation score – taking into account all dimensions.

Selection of cutoffs is based on two key concerns: (i) the nature of responses to different questions for corresponding indicators (binary, categorical, continuous), raising practical restrictions on the selection of cutoffs, and (ii) the motivation for inclusion (or exclusion) of responses in the definition of deprivation. For indicators with binary or categorical responses, I have taken a conservative approach, and allowed the identification function to take a value of 1 whenever the response is clearly indicative of deprivation. For example, for the indicator *school functionality*, both temporary and permanent closure of a school are considered to deprive the school. Conversely, for continuous responses such as number of teachers, student-teacher-ratio, among others, I have used existing literature to guide my selection process. Details on cutoffs z_j are provided in Table 3.

I choose conservative dimensional floors as thresholds. However, while some of them are straightforward (school is closed; no teachers in the school; SMC is not functional; less than one fan per classroom; more students than desks), others such as a student-teacher ratio (STR) of 50, or classroom-room ratio of 0.3 are more arbitrary, benchmark cutoffs.

Table 3: Description of Dimensions, Indicators, and Cutoffs

Dimension	Indicator	Weight	Cutoff
School status	Functional	1/23	School is temporarily or permanently closed
Infrastructure and Facilities	Building structure	1/23	Building structure appears to be dangerous for occupants
	Boundary wall	1/23	The wall is either absent, or dangerous for passersby
	Electricity	1/23	The school is not connected to the grid, or does not receive any electric supply from the grid
	Fans	1/23	Less than one fan per classroom in the school
	Facilities Index	1/23	Facilities include water pump, computer/science/physics/chemistry/biology/home economics labs, library, playground, medical first aid equipment and sports equipment. Cutoff: schools have access to less than three facilities
	Toilets	1/23	Bathroom facility is unavailable
	Student-functional toilet ratio	1/23	More than 30 students to every functional toilet in the school
	Water	1/23	Drinking water is unavailable in the school
Teachers	Teacher qualification	1/23	School-level average teacher qualification is less than required for grade being taught
	Teacher experience	1/23	School-level average teaching experience is less than 5 years
	Total # of teachers	1/23	There are no teachers in the school
	Student-teacher ratio	1/23	Student-teacher ratio is higher than 50 students to a teacher
Classrooms	# of Classrooms	1/23	There are no classrooms in the school
	Room utilization	1/23	Classroom-Room ratio at the school is less than 0.3 (there is less than one classroom to every three rooms in the school)
	Students per classroom	1/23	More than 40 students per classroom
	Blackboard	1/23	Some classrooms in the school do not have blackboards
	Chairs for students	1/23	There are more students than chairs so some students do not have access to a chair
	Desks for students	1/23	There are more than three students to each desk
	Chairs for teachers	1/23	There are more teachers than chairs (so some teachers do not have access to a chair)
	Desks for teachers	1/23	There is more than one teacher to a desk (so some teachers do not have a desk)

Community Engagement	School Management Committee (SMC) functional	1/23	SMC is not functional
	SMC funds	1/23	SMC funds were not disbursed to the respective SMC in FY 2014-15

Choices of weights and cutoffs are not trivial. Variation in k can generate significant variation in the $MSDI$ measure. A low k can lead to a high measurement for overall deprivation, while a high k can lead to a low measurement for deprivation. However, the key is to establish rules for weights and cutoffs and use them over at least a few years. This allows for comparisons across time related to both the overall $MSDI$, as well as performance within subgroups and dimensions. Frequent switching of these parameters makes it difficult to compare results over time, limiting the ability of policymakers to assess sectoral health.

A similar issue arises with varying weights over time. Arguably, one could use data-driven techniques and estimate weights using regression-based methods or factor analysis. However, the correlations uncovered by these methods are sensitive to a given time period, as well as the level of geographic aggregation. If estimated weights vary across time, then it would not make sense to maintain the same weights longitudinally. In this case, comparing sectoral health across years is akin to comparing apples with oranges. Similarly, if estimated weights vary by geographic aggregation as they plausibly do, then intra-region comparisons using the same region-level weights faces a similar issue.

The variable choice of cutoffs z, k, and weights w provides a valuable opportunity to policymakers, politicians, and citizens of a country to evaluate, assess, and impose their preferences and priorities on the evolution of schools in the country. This process of consensual calibration of the $MSDI$ allows for the index to be reflective of contextual expectations and aspirations. For simplicity, I take $k = 0.5$, which combined with the uniformity of the distribution of weights implies that for a school to be deemed multidimensionally deprived, it must be deprived in at least $13/23$ indicators. The sensitivity of this measure is assessed in Section IV.

III Discussion of Results

This section provides summary statistics and results for the application of the constructed multi-dimensional sectoral deprivation index (MSDI) to public schools in Sindh in FY 2014-15.

III.A Descriptive Statistics

ASC data reveals that 13 percent of surveyed schools were found to be either temporarily or permanently closed. In terms of infrastructure and facilities, approximately one-third of school buildings appeared to be hazardous for occupants. Further, one-half of schools either did not have a boundary wall, or the boundary wall was hazardous for passersby. The absence of boundary walls can impede student and teacher security.

I also find that 62 percent of schools were not connected to the electricity grid, and 47 percent of schools had more classrooms than fans, indicating that there were at least some spaces where there were no fans. In a province where summers are long and hot – temperatures frequently cross a hundred degrees Fahrenheit – the lack of electricity connections and fans in classrooms can cause acute discomfort to students and teachers during hot school hours. 46 percent of schools did not have access to a bathroom – students would be forced to defecate in other locations, such as open fields. Even for schools where there were functioning bathroom facilities available, 87 percent of schools had more than 30 students per functioning washroom. One-half of schools did not have access to drinking water.

Table 4: Summary Statistics

Sr. #	**Indicators**	**Deprivation Matrix**		**Censored Deprivation Matrix**	
		Mean	**SD**	**Mean**	**SD**
1	School is temporarily or permanently closed	13%	34%	46%	50%
2	Building structure appears to be dangerous for occupants	29%	45%	63%	48%
3	The wall is either absent, or dangerous for passersby	50%	50%	86%	35%
4	The school is not connected to the grid, or does not receive any electric supply from the grid	62%	48%	94%	23%
5	Less than one fan per classroom in the school	47%	50%	54%	50%

6	Washroom facility is unavailable	46%	50%	89%	31%
7	More than 30 students to every functional toilet in the school	87%	34%	96%	19%
8	Drinking water is unavailable in the school	51%	50%	88%	32%
9	School-level average teacher qualification is less than required by statutes for grade being taught	17%	37%	14%	35%
10	School-level average teaching experience is less than 5 years	7%	25%	9%	29%
11	There are no teachers in the school	13%	34%	46%	50%
12	Student-teacher ratio is higher than 50 students to a teacher	29%	45%	59%	49%
13	There are no classrooms in the school	16%	36%	44%	50%
14	Classroom-Room ratio at the school is less than 0.3 (there is less than one classroom to every three rooms in the school)	0%	6%	0%	5%
15	More than 40 students per classroom	38%	48%	56%	50%
16	Some classrooms in the school do not have blackboards	28%	45%	43%	49%
17	There are more students than chairs (so some students do not have access to a chair)	99%	8%	100%	4%
18	There are more than three students to each desk	77%	42%	95%	22%
19	There are more teachers than chairs (so some teachers do not have access to a chair)	29%	45%	72%	45%
20	There is more than one teacher to a desk (so some teachers do not have a desk)	50%	50%	84%	37%
21	Facilities include water pump, computer/science/physics/chemistry/biology/home economics labs, library, playground, medical first aid equipment and sports equipment. Cutoff: schools have access to less than three facilities	97%	17%	100%	2%
22	SMC is not functional	18%	38%	54%	50%
23	SMC funds were not disbursed to the respective SMC in FY 2014-15	39%	49%	74%	44%

In 17 percent of schools, the average teacher qualification was less than what is required required by prevailing statutes. An undertrained teacher would be one teaching elementary school but being untrained; teaching middle school but only having a Primary Teaching Certificate (PTC) or less; teaching secondary school but having a Certificate of Teaching (CT) or less; or teaching secondary or higher secondary school without having at least a Bachelor's degree.

Teachers while underqualified, have been holding positions for a relatively long tenure, on average. 93 percent of schools have teachers with an average tenure of greater than or equal to five years. 13 percent of schools were open but did not have a teacher present. For approximately one-third of schools, the student-teacher-ratio (STR) is greater than 50 students to a teacher. I also look at the student-to-classroom (STC) ratio, to get a sense of how crowded classrooms are in Sindh province, and find that approximately 38 percent of schools have STC of 40.

16 percent of schools do not have formal classroom. Thus, typical classroom activities would take place in makeshift classrooms, under palm trees or tin foil structures. In terms of classroom facilities, I find that more than 28 percent of schools have at least one classroom without a blackboard – a key medium of instruction. Almost all schools have at least one classroom with more students than chairs, so some students sit on the floor, while 77 percent of schools have at least some classrooms where more than three students use one study desk. These desks at the primary level are small, so more than three children per desk implies that some students do not have access to desk space for books and stationery. On the other hand, 29 percent of schools have some teachers who do not have access to chairs, while half of the schools have at least some teachers who do not have access to tables.

Auxiliary facilities include water pumps; computer, science, physics, chemistry, biology, and home economics labs; libraries; playgrounds; medical and first aid equipment; and sports equipment. I construct an index of these facilities, with deprivation on the index indicated by schools having access to less than three out of these eleven facilities. I find that 97 percent of schools are deprived in terms of extra facilities. As discussed earlier, there is empirical evidence that these facilities have a positive and significant impact on student outcomes. Therefore, this is a high level of deprivation and an obvious target for policymakers.

Besides school-level inputs, the participation of parents and the broader monitoring of school administration by the community are seen in the literature to positively influence school outcomes. Therefore, I focus on School Management Committees (SMC), which comprise teachers, parents and other community members, and are responsible for developing School Improvement Plans (SIP), hiring temporary teachers, and ensuring that transportation is provided to students so that they can get to school. I find that 18 percent of SMCs in the province (all schools are expected to have one) are not functional. Further, SMC funding was not disbursed to approximately two-fifths of all SMCs.

III.B Preliminary Results

Based on the selected dimensions, cutoffs, and weights associated with each dimension, the overall $MSDI$ for public schools for FY 2014-15 in Sindh clocks in at 0.17. Further, approximately 27 percent of schools in Sindh are deprived. On the other hand, the average deprivation score of deprived schools is 0.64. Thus, the deprivation intensity across deprived schools is high.

Further, I exploit the decomposition properties of the $MSDI$, and perform decompositions across subgroups such as the six administrative divisions and 28 administrative districts, [4] as well as decompositions across school classifications such as location (rural/urban), gender (boys/girls/mixed), and medium of instruction (Sindhi/English/Urdu). I also implement decompositions across each of the dimensions considered, to explore their contribution to overall school deprivation in Sindh province. I augment this with a division-wise, dimensional decomposition, to see how these contributions change across divisions of Sindh province. Table 5 provides results of the decomposition across divisions. Note that whenever the percentage contribution of a division to the overall $MSDI$ is greater than the population share (of schools) of the division, then the division contributes disproportionately to the $MSDI$. Fitting this criterion should raise a red flag and serve as a target for policymakers.

Table 5: Division-wise Decomposition Statistics

Division	Sample Size	HC Ratio (Poverty Incidence)	Poverty Intensity (Average Deprivation Score)	Multidimensional Sectoral Deprivation Index (MSDI)	Population Share (%)	Percentage contribution to MSDI (%)
Hyderabad	12,760	0.27	0.63	0.17	27.7%	27.2%
Karachi	3,099	0.06	0.61	0.04	6.7%	1.5%
Larkana	7,037	0.34	0.63	0.22	**15.3%**	**19.3%**
Mirpurkhas	8,411	0.39	0.65	0.25	**18.3%**	**27.2%**
SBA at Nawabshah	8,086	0.23	0.64	0.15	17.6%	15.1%
Sukkur	6,678	0.18	0.62	0.11	14.5%	9.6%

[4] In descending order, administrative sub-units of Pakistan include federal, provincial, district, tehsil/town, union, mauza.

I find that the highly urbanized division of Karachi contributes 6.7 percent to the overall school population in the province but contributes only 1.5 percent to the deprivation level of schools in the province. Similarly, Sukkur division contains 14.5 percent of schools in the province, but its contribution to the school deprivation score is 9.6 percent. On the other end of the spectrum, the eastern, lower riparian division of Mirpurkhas contains 18.3 percent of schools in the data, but its contribution to the overall school deprivation score is 27.2 percent. These results are also illustrated in Figure 3. Divisions above, and to the left of the 45-degree line contribute disproportionately more to the $MSDI$.

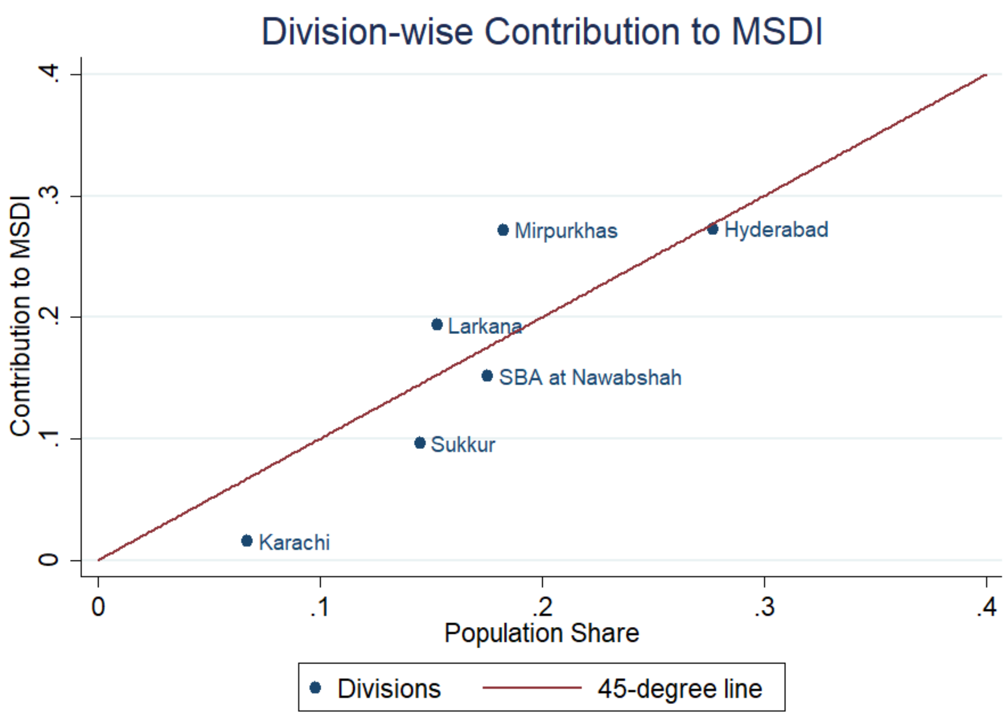

Figure 3: Division-wise Contribution to MSDI

Geographic regions can be further disaggregated for more targeted resource allocation. Table 6 disaggregates key $MSDI$ statistics from the division to the district level. It is clear that districts Dadu, Thatta, Mirpur Khas, Tharparkar, Sanghar, Jacobabad, Shikarpur, Umerkot, Kashmore, Kambar-Shahdadkot, and Sujawal contribute disproportionately to the overall deprivation score. Amongst these, Tharparkar, Sujawal, and Kashmore are of particular concern. Population shares and percentage contribution to overall $MSDI$ for these three districts are, 8.7%, 3.6% and 3.2%, and 15.4%, 6.7% and 6.7%, respectively.

Table 6: District-wise Decomposition Statistics

District	**Sample Size**	**HC Ratio (Poverty Incidence)**	**Poverty Intensity (Average Deprivation Score)**	**Multidimensional Sectoral Deprivation Index (MSDI)**	**Population Share (%)**	**Percentage contribution to MSDI (%)**
Badin	3,052	0.22	0.59	0.13	6.6%	5.0%
Central Karachi	617	0.04	0.59	0.02	1.3%	0.2%
Dadu	2,106	0.28	0.63	0.18	**4.6%**	**4.7%**
East Karachi	302	0.04	0.59	0.02	0.7%	0.1%
Ghotki	1,961	0.27	0.61	0.17	4.3%	4.1%
Hyderabad	881	0.06	0.59	0.04	1.9%	0.4%
Jacobabad	1,440	0.37	0.59	0.22	**3.1%**	**4.0%**
Jamshoro	788	0.24	0.66	0.16	1.7%	1.6%
Kambar-Shahdadkot	1,631	0.31	0.65	0.20	**3.5%**	**4.1%**
Kashmore	1,495	0.54	0.65	0.35	**3.2%**	**6.7%**
Khairpur Mirs	3,460	0.14	0.65	0.09	7.5%	4.1%
Korangi Karachi	610	0.05	0.57	0.03	1.3%	0.2%
Larkana	1,171	0.09	0.58	0.05	2.5%	0.8%
Malir Karachi	637	0.12	0.63	0.07	1.4%	0.6%
Mirpur Khas	2,169	0.30	0.64	0.19	**4.7%**	**5.2%**
Mitiari	926	0.15	0.64	0.09	2.0%	1.1%
Naushero Feroze	2,333	0.18	0.64	0.12	5.1%	3.4%
Sanghar	3,126	0.29	0.64	0.19	**6.8%**	**7.4%**
Shaheed Benazirabad	2,627	0.20	0.64	0.13	5.7%	4.3%
Shikarpur	1,300	0.35	0.65	0.23	**2.8%**	**3.8%**
South Karachi	547	0.06	0.63	0.04	1.2%	0.3%
Sujawal	1,644	0.50	0.64	0.32	**3.6%**	**6.7%**
Sukkur	1,257	0.14	0.61	0.08	2.7%	1.4%
Tando Allah Yar	831	0.16	0.63	0.10	1.8%	1.1%
Tando Muhammad Khan	1,017	0.23	0.59	0.14	2.2%	1.7%
Tharparkar	4,009	0.46	0.66	0.30	**8.7%**	**15.4%**
Thatta	1,515	0.38	0.67	0.26	**3.3%**	**4.9%**
Umerkot	2,233	0.36	0.64	0.23	**4.8%**	**6.5%**
West Karachi	386	0.05	0.60	0.03	0.8%	0.2%

These results are further explored in Figure 4. Divisions Hyderabad, Larkana, and Mirpurkahs appear to be the worst-performing divisions in terms of school-level resources, with a large fraction of their constituent districts lying above the 45-degree line. Note that Hyderabad, in terms of aggregate $MSDI$, did not raise a red flag in the division-wise analysis. This reveals that there is substantial variation in school-level deprivation across districts within Hyderabad division.

On the other extreme is division Karachi, which is also the urban, commercial and financial center of Sindh province. All districts of division Karachi lie well below and to the right of the 45-degree line, indicating a much lower contribution to the provincial $MSDI$ as compared to the districts' contribution to the set of schools. Divisions SBA at Nawabshah and Sukkur both appear to perform better than their counterparts, but not as well as division Karachi.

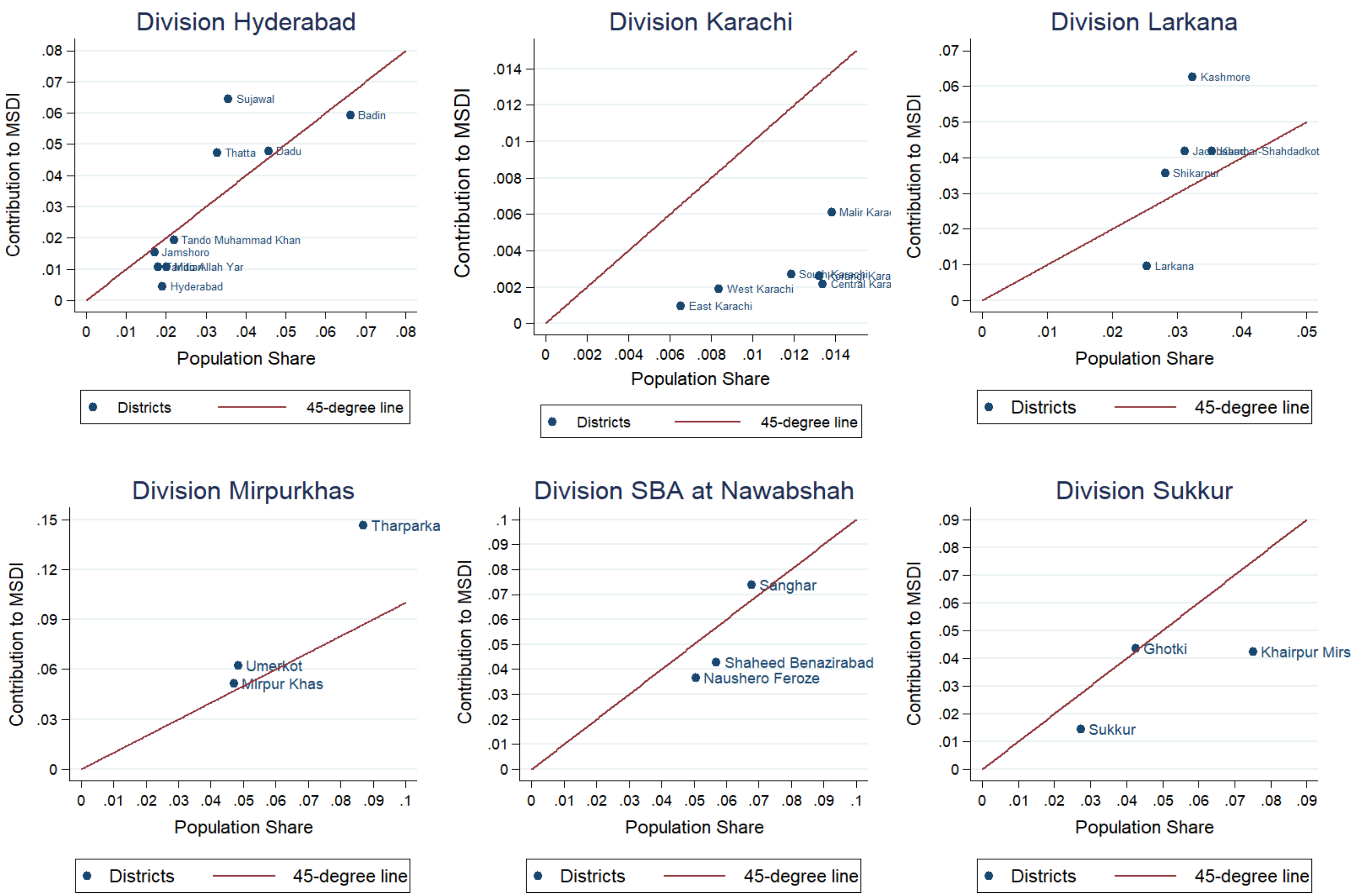

Figure 4: District-wise Contribution to MSDI (by Division)

Decompositions by location, gender and medium of instruction reveal interesting patterns. Urban schools comprise 10.2 percent of all schools in the province, but their contribution to the overall $MSDI$ score is 2.6 percent. Therefore, rural schools contribute disproportionately (97.4 percent) to school deprivation in the province. Further, single-gender schools contribute disproportionately to the overall score on the $MSDI$, as compared to mixed-gender schools. Boys-only and girls-only schools comprise 23.1 percent and 15.3 percent of all schools, respectively. However, their respective contributions to the overall $MSDI$ score are 29.7 percent and 19.7 percent, respectively. 61.6 percent of schools are mixed-gender. However, their contribution to the overall deprivation score stands at 50.6 percent.

In terms of medium of instruction, Urdu and English medium schools comprise approximately one-tenth of schools in Sindh. However, their contribution to the $MSDI$ score is even lower, at 3.5 percent. On the other hand, most schools are Sindhi-medium, and contribute 96.3 percent to the overall deprivation score. These results are provided in Table 7 and are illustrated in Figure 5. Sindhi-medium, single-gender, rural schools lie below and to the right of the 45-degree line, suggesting that they are the least resourced as compared to their subgroup counterparts.

Table 7: Other Subgroup-wise Decomposition Statistics

Classification	**Subgroup**	**Sample Size**	**HC Ratio Poverty Incidence**	**Poverty Intensity (Average Deprivation Score)**	**Multidimensional Sectoral Deprivation Index (MSDI)**	**Population Share (%)**	**Percentage contribution to MSDI (%)**
Location	Urban	4,707	0.07	0.61	0.04	10.2%	2.6%
	Rural	41,364	0.29	0.64	0.19	**89.8%**	**97.4%**
Gender	Boys	10,625	0.33	0.66	0.22	**23.1%**	**29.7%**
	Girls	7,069	0.33	0.66	0.22	**15.3%**	**19.7%**
	Mixed	28,377	0.23	0.61	0.14	61.6%	50.6%
Medium	Urdu	3,246	0.07	0.60	0.04	7.0%	1.8%
	Sindhi	41,274	0.29	0.64	0.18	**89.6%**	**96.5%**
	English	1,551	0.14	0.64	0.09	3.4%	1.7%

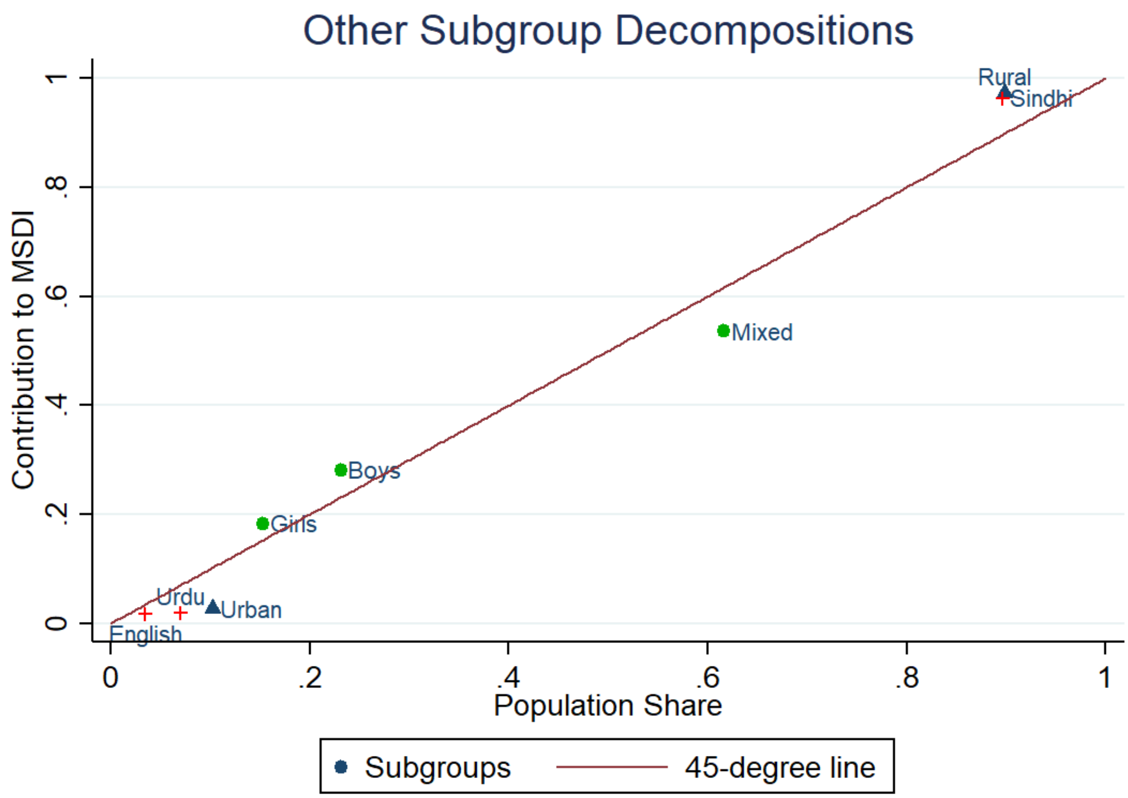

Figure 5: Other Subgroup-wise Contribution to MSDI

While subgroup decompositions provide geographical targets for enhanced fiscal and policy interventions, dimensional decompositions shine a light on areas within schools that are the worst resourced and causing the highest level of deprivation. Given that each of the 23 indicators are equally weighted, the dimensions that contain the highest number of indicators are likely to make the highest contribution to the overall *MSDI* score, as compared to other dimensions. Therefore, a more informative approach is to study the contribution of each indicator within these dimensions to the overall *MSDI* score. Figure 6 provides a snapshot of the performance of schools on each indicator.

I find that school status; teacher qualification, experience and number of teachers; number of classrooms, room utilization, and blackboards; and functionality of SMCs contribute disproportionately less to the overall *MSDI* score. Conversely, boundary walls, electricity, facilities index, toilets, student to functional toilet ratio and drinking water; chairs for students, desks for students and teachers; and SMC funds disbursement contribute disproportionately more to overall deprivation. Specific statistics can be found in Appendix 1.3, Table 1. Such a decomposition can be replicated for each division to generate dimensional maps providing a powerful visual tool for targeted policymaking.

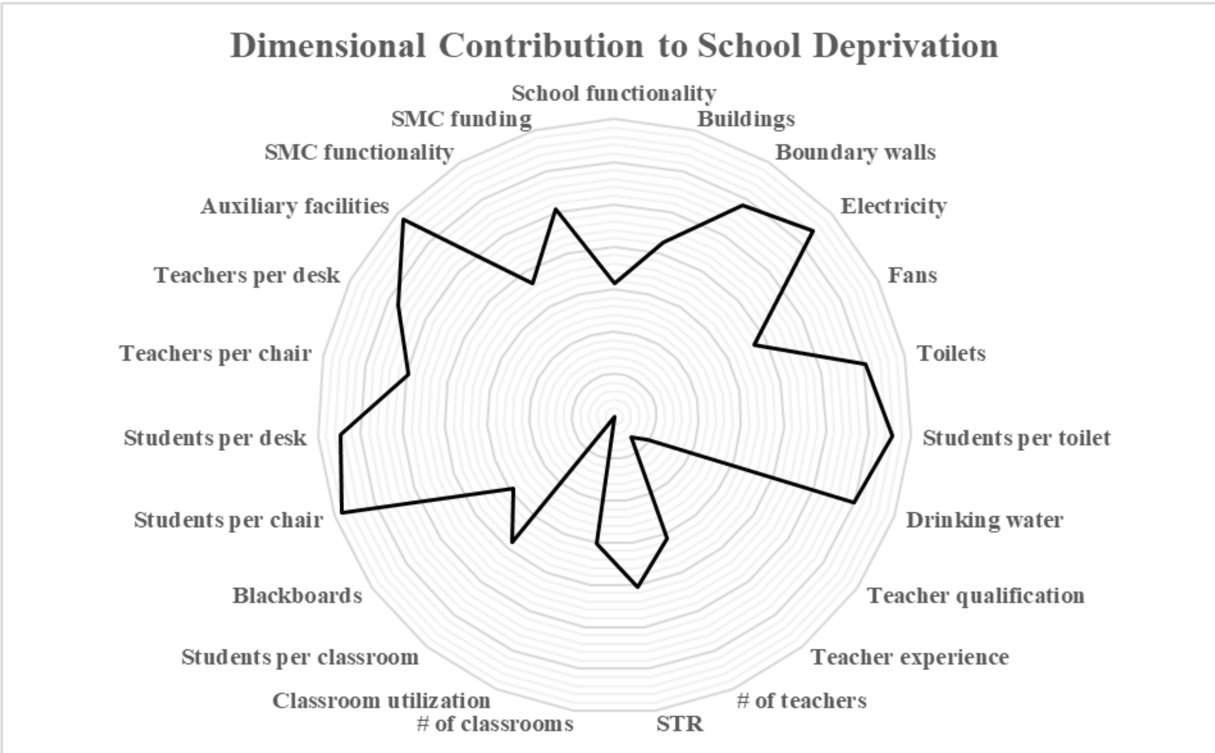

Figure 6: Contribution to MSDI per Indicator

Table 8 compares dimensional breakdowns across divisions. For example, I find that the contribution of school status to the overall score is the lowest in Karachi (0.1 percent) while its contribution from Mirpurkhas (1 percent) is the highest. Similarly, community engagement contributes the most to the overall score from Mirpurkhas (2.4 percent) as compared to Karachi (0.1 percent). These results are illustrated in Figure 7.

Table 8: Dimensional Contribution to MSDI (by Division)

		Dimensions				
	Division	**School Status**	**Infrastructure and Facilities**	**Teachers**	**Classrooms**	**Community Engagement**
1	Hyderabad	0.9%	12.8%	2.4%	8.9%	2.3%
2	Karachi	0.1%	0.7%	0.1%	0.5%	0.1%
3	Larkana	0.5%	8.9%	1.5%	6.7%	1.6%
4	Mirpurkhas	1.0%	12.2%	2.5%	9.2%	2.4%
5	SBA at Nawabshah	0.5%	6.8%	1.3%	5.1%	1.5%
6	Sukkur	0.3%	4.3%	1.0%	3.2%	0.8%

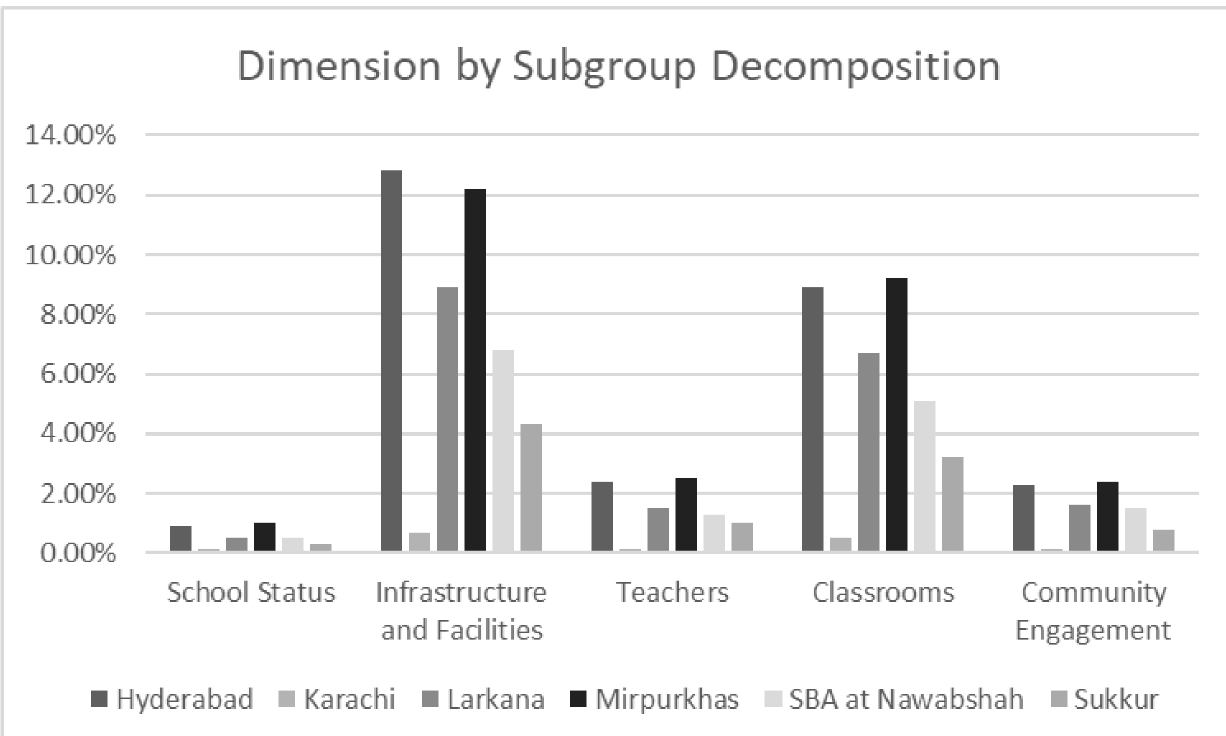

Figure 7: Dimensional Contributions to MSDI (by Division)

IV Sensitivity Analysis

Recall that the deprivation score vector c contains scores for each sectoral unit given by $c_i = \sum_{j=1}^{d} w_j g_{ij}^0$. Using constant weights for convenience for each of the indicators reduces this to $c_i = \frac{1}{23}\sum_{j=1}^{d} g_{ij}^0$. However, in practice, these weights can vary, based on the relative importance of the set of indicators used. To assess how the $MSDI$ score will change based on variation in these weights, I run a Monte Carlo simulation and generate a distribution of the overall $MSDI$ score.

For each round of the simulation, I draw a random weight for each indicator with $w_i \sim U(0,10)$, without replacement. I then normalize the weights by dividing each weight by the sum of all twenty-three randomly drawn weights. Thus, each random normalized weight is $W_i \in [0,1]$ and $\sum_{j=1}^{23} W_j = 1$. Using these simulated weights, I calculate a new deprivation score c_i for each school in the application, and then follow the process explained in section I.A to calculate the respective sample $MSDI$. I repeat the process a total of 500 times, leading to a distribution comprising 500 $MSDI$ scores. I then compare the mean of this distribution with the $MSDI$ score that I obtained using uniform weights to provide a measure of sensitivity to the results of the analysis with constant weights.

I also conduct the same sensitivity analysis for the fraction of deprived schools H, and the intensity of deprivation A. For each of these constituents of the $MSDI$, I compare the means of their distributions with the values for H and A which I obtained using uniform weights. I repeat the process by also altering the overall deprivation score cutoff k, with $k \in \{0.25, 0.5, 0.75\}$. Recall that deprivation scores c_i that are less than k are suppressed to 0.

Figure 8 provides the results of the sensitivity analysis. Each column of graphs corresponds to a particular k value, while each row of graphs takes as its independent variable the $MSDI$, H, and A statistics, respectively. The graphs have been smoothed using an efficient Epanechnikov kernel. The solid vertical lines indicate the measurement of the statistic based on uniform w_i's. The dotted vertical lines are the mean statistics obtained from the Monte Carlo simulation. It is obvious that for different values of k, the statistics obtained under the strong assumption of uniform weights are very close to the simulated means of the statistics under varying weights. However, for $k = 0.25$, the means of the simulated A and H are marginally different from their measurements under uniform weights. However, these differences are economically small.

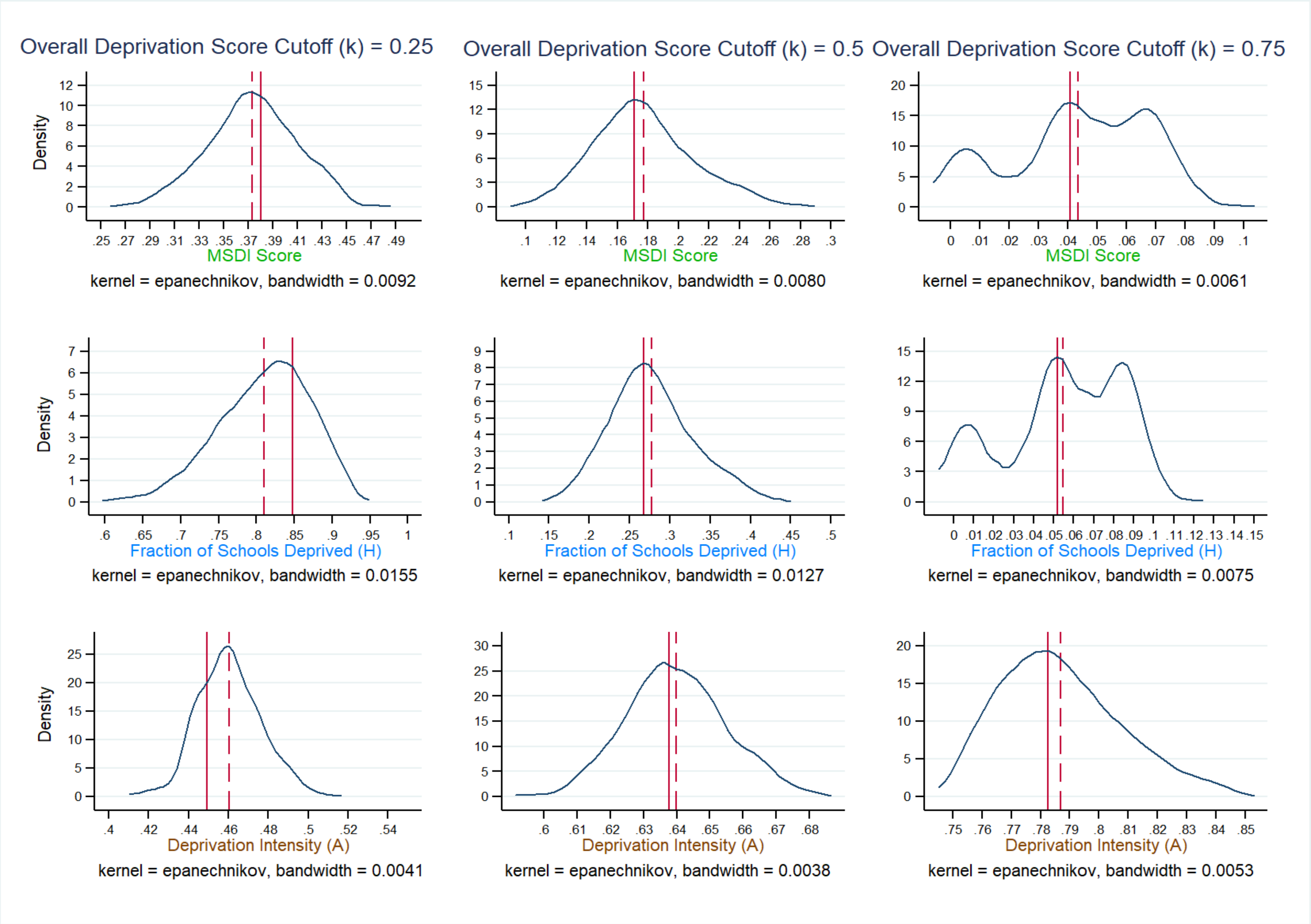

Figure 8: Sensitivity Analysis

The estimated statistics, however, are highly sensitive to the choice of the overall deprivation score cutoff k. Moving from $k = 0.25$ to $k = 0.75$, the mean of the simulated $MSDI$ scores ranges from 0.37 to 0.045. Similarly, the fraction of deprived schools ranges from 81% to 5.5%. This underlines the debate between choosing either an identification function $\rho_k(x_i; z)$ under the intersection or union approaches on the one hand, and a more flexible intermediate identification function on the other, as discussed in section I.A. The choice of an extreme identification function can understate (intersection) or overstate (union) multidimensional deprivation substantially. Therefore, the results of the simulation with varying k cutoff scores suggest that the intermediate approach would be preferred. As pointed out earlier, even with high sensitivity of the measure to k, the use of a consistent k across regions and time allows for strong cardinal comparisons to gauge improvements or worsening of the $MSDI$. Further, gradually reducing k and focusing on subgroups that persist in the fraction of those being deprived allow for clearer identification of the worst-performers.

V Conclusion

The development of the Multidimensional Sectoral Deprivation Index ($MSDI$) provides a unique method of synthesizing a large amount of information that policymakers face on a regular basis, when assessing sectoral health and resource base. The wide range of indicators related to sectoral inputs, processes and outcomes can make cross-regional and intertemporal comparisons difficult. The MSDI allows policymakers to glean useful information from the din of survey and administrative data.

For example, in the case of public education in Sindh province, should policymakers target those districts that are resourced poorly on some subset of infrastructure and school facilities rather than those districts which are resourced poorly on others? Should they be concerned more about districts performing poorly on indicators such as on teacher qualification, as compared to how they are performing on student-teacher ratios? How do policymakers reconcile these variations in education sector health related to school, classroom, student and teacher indicators? Given that policymakers in developing country contexts have access to scarce resources, it is important that they have a robust tool that allows them to measure sectoral health, unpack what they learn, and compare sectoral health and the resource base over time. The $MSDI$ serves as one such tool.

The $MSDI$ can be exploited by researchers and policymakers to focus on the most deprived sectoral units, with deprivation measured via the inclusion of a large number of indicators across a few key dimensions, to construct a single index of deprivation scores. The parameters leveraged by the tool can also be adjusted based on emerging research on what inputs have the largest impact on the performance of sectoral units, as well as on evolving normative concerns about the rights of citizens. However, the tool's capabilities are optimized when these parameters are held stable for a period of time to make longitudinal analysis possible. Thus, the $MSDI$ has high potential for entering the toolkit of policymakers and academics, when targeting sectoral units on the right-tail of the deprivation distribution.

During the development of the tool, I piloted its application to the case of public education in Sindh province, Pakistan, by using the Annual Census of Schools (ASC) from FY 2014-15. Results reveal a high level of deprivation, with subgroup and dimensional decompositions allowing for deeper insights into the regions, classifications and dimensions that are contributing the most to school deprivation in Pakistan.

There is substantial scope for expansion in this research agenda. Some avenues for further research include expanding data fed to the tool for inter-provincial, cross-country and intertemporal analyses; standardizing these scores based on community aspirations and expectations; and including other subgroups such as privates schools and madrassahs (religious schools) in the case of Pakistan. Another potential area of research is to assess the impact of policy interventions on the $MSDI$ by generating $MSDI$ scores with stable parameters over a period of time, and conducting reduced-form impact evaluations using the $MSDI$ as the outcome variable.

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Appendices

Appendix 1.1: Institutional Structure and Decentralization of Education in Pakistan

In recent years, political, fiscal and administrative roles and responsibilities related to the education sector have been decentralized in Pakistan. Prior to 2000, education was a primarily federal subject, with certain administrative responsibilities being delegated to the divisional, provincial or district levels. The first significant move towards decentralization did not substantially affect the share of responsibilities between the federal and the lower levels. Rather, it affected the distribution at the lower levels, between the provincial and the district levels[5], by making the district, instead of the provincial level the operational tier of governance. This change was promulgated by the provinces via the provincial promulgation of the Local Government Ordinance (LGO) in 2001.

The LGO followed the broader Devolution Plan of 2000 and devolved various responsibilities from the provincial to the district level. At the district level, the *Nazim* served as the chief executive, and the administration of the district as well as the police reported to him. In terms of the district's administration, the District Coordination Officer (DCO) was appointed to coordinate the workings of 12 different departments, one of which was education. Each of these departments was headed by an Executive District Officer (EDO), who reported to the DCO. The education department was to be headed at the district level by the EDO-Education (Khan et al., 2011). The education department was reflected at the provincial level as well, and was headed by the minster of education, with executive control vested in the education secretary. Following the promulgation of LGO, planning, monitoring and evaluation of education, as well as disbursement of salaries and the management of teaching and non-teaching staff was transferred to the district level. The provincial government is still responsible for the creation or elimination of different educational posts and positions. Further, the provincial government is responsible for devising the provincial

[5] In descending order, administrative sub-units of Pakistan include federal, provincial, district, tehsil/town, union, mauza.

plan for education, as well as to provide backstopping and technical capabilities to districts via specialized units within the provincial education department. An example is the Reform Support Unit within the Education and Literacy Department of Sindh province.

The next big step in the decentralization story was the enactment of the 18th Constitutional Amendment of 2010, a further transfer of responsibilities was made, this time from the federal to the provincial levels. The amendment removed shared responsibilities – such as curriculum, syllabus, planning, policy centers of excellence, standard of education, and Islamic education – between the provincial and federal levels from the concurrent list, and made them the sole responsibility of the provinces, thereby enhancing significantly, the strategic and policy-related responsibilities of the province. Following the amendment, the federal ministry of education underwent a number of name changes, with federal authorities finally settling on the Ministry of Federal Education and Professional Training in 2014. The ministry is primarily responsible for providing technical, vocational and professional skills and training, and collaborates with other organizations to create sponsorships and scholarships for students. Departments reporting to the ministry include the National Vocational and Technical Training Commission, National Commission for Human Development, National Education Foundation and the National Education Assessment System.

In terms of fiscal decentralization, the 18th Amendment required the federal government to provide provinces funding for education via the National Finance Award (NFA) – a formula that divides the revenue pie across the four provinces. However, tax revenues generated at the provincial level meet the major chunk of funding required for education at the provincial level. Certain projects and reforms are funded by loans, grants or assistance of bilateral and multilateral agencies. Specifically, districts are funded by own-revenue, provincial non-earmarked block grants, and ad-hoc education grants provided the federal level. It is important to note that the DCO is the principal accounting officer, and all funds flow through his or her office.

Appendix 1.2: Sindh Education Management Information System (SEMIS)

The Sindh Education Management Information System (SEMIS) is a derivative of the National Education Management Information System (NEMIS). NEMIS was established in 1990 at the federal level, with the assistance of the United Nations. The purpose of NEMIS was to collect key information on education indicators across the country, and to serve as the national education data repository. Starting 1992, NEMIS has produced the Pakistan Education Statistics, a key national report annually.

By the end of 1993, funding for NEMIS started diminishing, leading provinces to look inwards in terms of setting up semi-autonomous bodies that could play the role of NEMIS at the local level. In Sindh, this led to a collaboration between the Government of Sindh (GoS) and the World Bank, and the establishment of the SEMIS in 1994. The partnership ended in 1996, with SEMIS being shifted from development to non-development funding, under the supervision of the provincial education department.

In 2006, following the devolution of power in Pakistan, the Sindh government decided to consolidate provincial education data under the Reform Support Unit (RSU) housed in the Education and Literacy department of Sindh province. The RSU was a new semi-autonomous body, which was also charged with monitoring and evaluation, and policy implementation of educational reforms in the province, and started with seed funding of PKR 50 million, or approximately USD 800,000. The RSU included three separate wings: SEMIS wing, monitoring and evaluation wing, and the policy wing. The SEMIS wing was also responsible for conducting the Annual School Census (ASC), a universal survey of all public schools in the province. With the development of province-level EMIS structures, the NEMIS took on the role of consolidating data from the provinces and the special regions and developing national level statistics and reports.

In its current form, the RSU compiles data on all schools via the Annual School Census, links this with the EMIS, and maintains a GIS tool which users can use to point-and-click and go to statistics related to individual schools. Each school is identified by a unique SEMIS code.

New codes are assigned after a review process of the school, and old codes have been periodically revised to streamline the coding system.

Appendix 1.3: Tables for Additional Empirical Results

Table 1: Dimensional Breakdown of Deprivation

Dimensions	Indicators	Censored HC Ratio	Percentage Contribution	Dimension-wise Contributions	Mean Contribution per Indicator
School status	Functional	0.13	2.5%	2.5%	2.5%
Infrastructure and Facilities	Building structure	0.21	4.1%	47%	6%
	Boundary wall	0.29	5.8%		
	Electricity	0.32	6.4%		
	Fans	0.19	3.8%		
	Facilities Index	0.35	6.9%		
	Toilets	0.30	6.0%		
	Student-functional toilet ratio	0.33	6.7%		
	Water	0.29	5.8%		
Teachers	Teacher qualification	0.05	1.0%	8%	2%
	Teacher experience	0.03	0.7%		
	Total # of teachers	0.13	2.5%		
	Student-teacher ratio	0.18	3.6%		
Classrooms	# of Classrooms	0.14	2.8%	34%	4.5%
	Room utilization	0.00	0.0%		
	Students per classroom	0.19	3.9%		
	Blackboard	0.14	2.8%		
	Chairs for students	0.35	6.9%		
	Desks for students	0.32	6.5%		
	Chairs for teachers	0.21	4.3%		
	Desks for teachers	0.26	5.2%		
Community Engagement	School Management Committee (SMC) functional	0.15	3.0%	8%	4%
	SMC funds	0.23	4.5%		

Appendix 1.4: Additional Figures

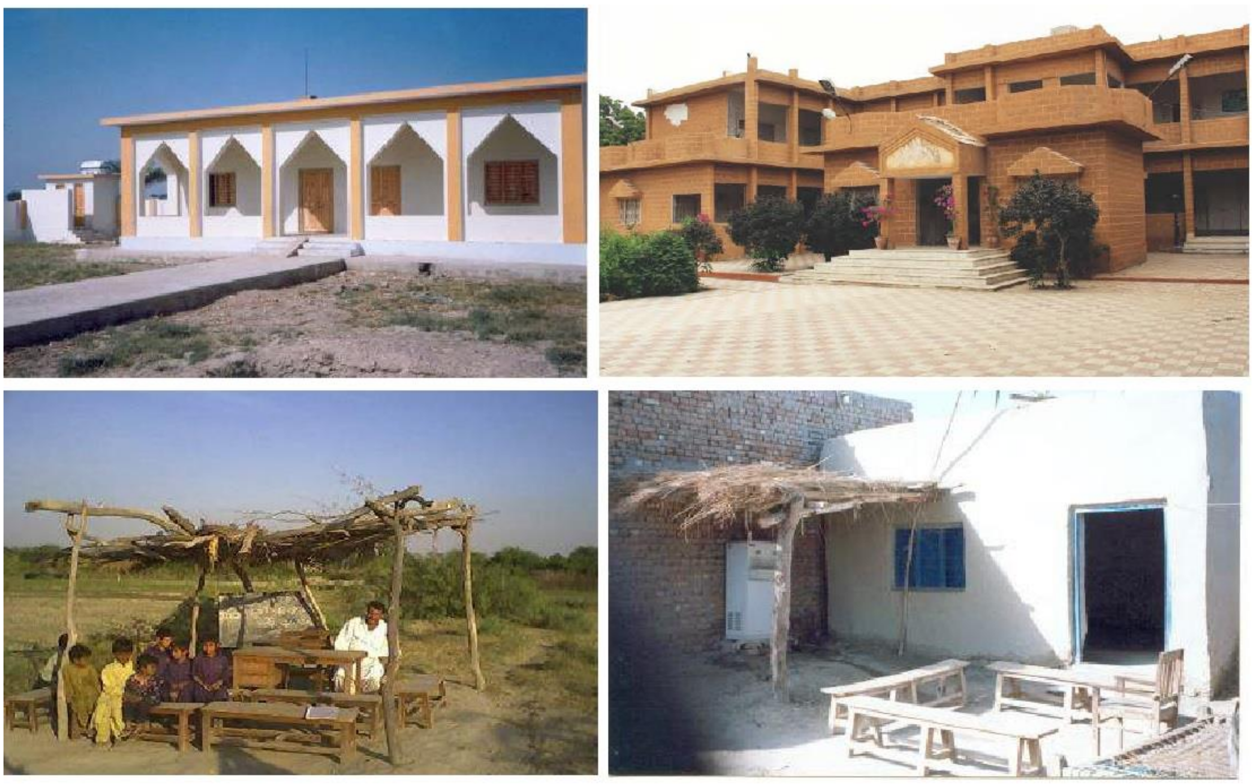

Figure 1: The Varying State of Schools in Sindh Province

25th Annual School Census 2015-16 پنجويهون ساليانو اسڪول شماري

Sindh Education Management Information System سنڌ ايجوڪيشنل مينيجمينٽ انفارميشن سسٽم

Reform Support Unit ريفارم سپورٽ يونٽ

Education & Literacy Department - Government of Sindh

تعليم ۽ خواندگي کاتو، حڪومت سنڌ

Proforma for Primary Schools

Page - 1

SEMIS Code سيمس ڪوڊ	

GPS Coordinates	
Lon (E)	
Lat (N)	
	D D D M M.M M M M

1. School's Basic Information اسڪول جي بنيادي معلومات

Reference Date 31st October 2015

a. Taluka تعلقو / Town ٽائون		b. Union council يونين ڪائونسل	c. Tappa ٽپو
d. Deh ديھ	e. N.A	f. P.S	g. Area علائقو / Village ڳوٺ
h. School name with prefix اسڪول جو نالو			
i. Address ايڊريس/ پتو			j. Phone: فون

2. Information about Data Provider اسڪول جي معلومات ڏيندڙ جا ڪوائف

a. Name نالو		b. CNIC شناختي ڪارڊ نمبر	— —
c. Designation عهدو	1=HM; هيڊ ماسٽر 2=Incharge; انچارج 3=Teacher; استاد 4=Other; ٻيا	d. Gender جنس	1=Male; مرد 2=Female; عورت
e. Contact No. (Tele/Mob) موبائل نمبر		f. Email-Address اي ميل ايڊريس	

3. School Status اسڪول جي حيثيت

Question سوال	Responses جواب	Code ڪوڊ
a. Type of School اسڪول جو قسم	☐ Viable; هلندڙ جوڳو ☐ Non-Viable; نہ هلندڙ جوڳو	
b. Detail Status تفصيلي حيثيت	1=Functional; فعال 2=Temporary Closed; عارضي بند 3=Permanent Closed; مستقل بند	
c. If 'Temporary Closed' OR 'Permanent Closed', then write the month & year of closure *[This option applied on both condition Viable & Non-Vialbe]*		
d. If 'Temporary Closed' OR 'Permanent Closed', then write code for major reason *[This option applied on both condition Viable & Non-Viable]*	1=Non availability of Teacher; 2=No Population / No Enrollment; 3=School ceases to function long time ago and no record available for this school (Not in existence); 4=Due to litigation; 5=Due to Law and order situation; 6=Any Other Specify ______	
4. Location هنڌ	1=Urban; شهري 2=Rural; ٻهراڙي	
5. Level درجو	1=Primary; پرائمري 9=Primary with Permission to run middle classes; پرائمري اسڪول مڊل ڪلاس هلائڻ جي اجازت نامي سان گڏ	
6. Is this school has approved Schedule New Expenditure (SNE)? ها جي لاءِ مقرر ٿيل، ڪم ڪندڙ ۽ خالي اسامين جي تعداد لکو	Code: 1=Yes; ها 2=No; نہ — SNE Staff ايس اين اي عملو: Teaching تدريسي عملو; Non-Teaching غير تدريسي عملو — Sanctioned Post مقرر ٿيل — Working Post ڪم ڪندڙ — Vacant Post خالي	
7. Administration اسڪول انتظاميه	1=TEO Male; ٽي اي او ميل 2=TEO Female; ٽي اي او فيميل 3=DO Local Bodies; ڊي او لوڪل باڊيز 4=BOC; بي او سي 5=Other specify ______; ٻيا	
8. Gender (Sex) جنس	1=Boys School; ڇوڪرن جو اسڪول 2=Girls School; ڇوڪرين جو اسڪول 3 = Mixed School; مخلوط اسڪول	
9. Medium [Multi Tick Allowed] and medium wise enrollment as on reference date. 31st Oct 2015 اسڪول جي ميڊيم جي نشاندهي ڪريو، هڪ کان وڌيڪ ميڊيم جي نشاندهي ڪري سگهجي ٿو.	Urdu Medium اردو ميڊيم ☐ Enrollment داخلا — Sindhi Medium سنڌي ميڊيم ☐ Enrollment داخلا — English Medium انگلش ميڊيم ☐ Enrollment داخلا	
10. Shift شفٽ	1 = Morning; صبح 2 = Afternoon; ٻيپهري 3 = Both Shifts; صبح ۽ ٻيپهري	
11. Is this a Campus School? ڇا هيءَ ڪيمپس اسڪول آهي؟ for yes write how many schools are merged? ها جي لاءِ ضم ٿيل اسڪولن جي تعداد لکو	1=Yes; ها (No. of Merged Schools; ______) 2=No; نہ	

Figure 2: Sindh ASC Data Collection Form for Primary Schools (Sample)